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Research Article

Accounting Information Disclosure and Financial Crisis Beforehand Warning Based on the Artificial Neural Network

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With the continuous development of China's market economy, market competition has become increasingly fierce. In this context, enterprises will face more and more problems. Among them, the financial crisis is undoubtedly the most significant and the biggest problem that threatens the survival and development of enterprises, and it is an unavoidable problem for all enterprises. Irregular accounting information disclosure is an important factor that leads to the financial crisis of enterprises. Because accounting information contains a lot of important financial information within the enterprise, if the information is not disclosed in compliance with the norm, it will cause immeasurable financial crisis to the enterprise. Therefore, it is of great significance to establish an effective financial crisis beforehand warning system and avoid the noncompliant disclosure of accounting information in order to avoid and control the occurrence of financial crisis in enterprises that threaten the survival and development of enterprises. At present, artificial neural network technology is constantly developing and improving with the development of science and technology, and it has been proven that it has remarkable performance for handling nonlinear data, which provides new ideas and technical support for enterprises' financial crisis beforehand warning. This article is aimed at studying accounting information disclosure and financial crisis beforehand warning based on an artificial neural network. Based on the BP learning algorithm of the artificial neural network, an accounting information disclosure test and financial crisis beforehand warning model were constructed, and with the help of this model, the accounting information disclosure test and financial crisis beforehand warning experiment with H company as an example were carried out, and the conclusions were drawn: the accounting information disclosure test and financial crisis beforehand warning model based on the artificial neural network BP learning algorithm reduce the company' s financial loss by 8% by reducing the company' s noncompliant accounting information disclosure rate, and the accuracy rate of the company' s financial crisis beforehand warning is also increased by 35%.

1. Introduction

The changes in the market competition environment brought about by economic globalization and the rapid development of China's market economy have led to increasingly fierce market competition. In such an economic environment, enterprises and listed companies are very likely to encounter financial crises. Financial crisis is a major problem that can directly affect or threaten the survival and development of enterprises and listed companies among all the problems that enterprises or listed companies will face. Once an enterprise or company has a financial crisis, it is very easy to cause the enterprise or company to suffer huge economic losses, and even the losses suffered will directly lead to the demise of the enterprise or company. Therefore, avoiding financial crisis is of great significance to the survival and development of enterprises and companies. Furthermore, after the financial crisis of 2008, corporations have become increasingly aware of the fragility of the entire financial and economic system. The fragility of the financial system's economic system means that if a large number of companies are caught in an unfathomable financial crisis at the same time, it is likely to trigger a new financial crisis, which in turn will cause huge turbulence in the global economy. Therefore, more and more domestic and foreign enterprises and companies have regarded strengthening the early warning and prevention of financial crisis as an important measure to prevent financial crisis. Irregular accounting information disclosure is a major cause of financial crisis in enterprises or companies. Therefore, more and more enterprises and companies are trying to establish an effective accounting information protection system and financial crisis beforehand warning system before the outbreak of the economic crisis, so as to strengthen the supervision and control of the financial factors of enterprises or companies with potential threats, so as to prevent problems before they occur. The current main financial crisis beforehand warning methods can be briefly summarized as traditional statistical methods and artificial intelligence methods. The advantage of the traditional statistical method is that the specific analytical formula can be obtained simply and intuitively, and it has certain advantages in understanding the entire financial crisis beforehand warning model. However, its defect lies in the strict restrictions on independent variables, which often require independent variables to meet a series of statistical characteristics. And the assumptions of traditional statistical methods are only a special case of the actual situation, sometimes far from the actual economic situation. This makes the traditional statistical model unable to fit the actual data well, thus lacking convincing. Among the artificial intelligence methods, the utilization of artificial neural network model is the most representative. An artificial neural network, regarded as a neural network, is a mathematical model that imitates a biological neural network for information handling. The artificial neural network has strong information and data handling advantages, so it has been widely used in various fields, and it also has certain application value for preventing noncompliant accounting information disclosure and financial crisis beforehand warning.

The innovation of this study is that (1) taking H company as an example, it explores its accounting information disclosure and financial crisis beforehand warning based on the artificial neural network. (2) Based on the artificial neural network BP learning algorithm, an accounting information disclosure test and financial crisis beforehand warning model were established, and with the help of this model, the accounting information disclosure test and financial crisis beforehand warning experiment of H company from 2018 to 2021 were carried out, and the results were obtained.

2. Related Work

Since the artificial neural network has certain application value in various fields, many researches related to the artificial neural network have emerged in the academic circle in recent years. Among them, Alanis studied the application of a Kalman filter loop training algorithm based on the artificial neural network in electricity price and verified the applicability of the prediction scheme he proposed through experiments [1]. Isik combined with artificial neural network technology to carry out research on a meteorological data forecasting system. He modeled the data obtained from the General Administration of Meteorology through artificial neural networks and an adaptive network-based fuzzy inference system and proposed an effective weather forecasting system [2]. Khorasani and Yazdi's research focuses on the prediction of dynamic surface roughness during metal cutting operations. They proposed a general dynamic surface roughness monitoring system for metal cutting operations based on artificial neural networks [3]. Safa et al. studied the role of artificial neural networks in simulating wheat production. They eventually developed an artificial neural network model capable of directly using direct and indirect technical factors to predict wheat yield under different conditions and farming systems [4]. Tarawneh developed an artificial neural network model to predict the value of N60 based on GPT data through his research, and the experiment proved that the model has good accuracy and acceptability [5]. Li et al. studied how to use neural networks to control grid-connected rectifiers/inverters to alleviate the limitations of three-phase grid-connected converters in renewable energy and power system applications and proposed an effective artificial neural network based the neural vector control strategy of the network [6]. Although these studies are closely related to artificial neural networks, the research angles of these studies are relatively single, which results in insufficient practicality of the research conclusions.

3. Accounting Information Disclosure and Financial Crisis Beforehand Warning Based on the Artificial Neural Network

3.1. Artificial Neural Networks. The artificial neural network, also known as a neural network, is an emerging interdisciplinary subject developed on the basis of studying the learning ability and operating mechanism of biological neural networks. The neural network is a mathematical model that imitates a biological neural network for information handling, which originated in the 1940s [7]. Neural networks have strong computing power and can simultaneously complete many learning tasks and solve many specific problems. At the same time, the information processing ability of the artificial neural network is also strong, and it can make relevant processing on the input data and information according to the specified requirements. The artificial neural network is connected by many physical cell units according to certain rules, and the structure of its physical cell units is very simple. The working principle of the artificial neural network is that all cell units participate in the dissemination and handling of information at the same time, and this way is consistent with the way the biological neural network processes information. Neural networks also store information in the connected structures of individual physical cell units. Therefore, it can be said that the artificial neural network is a physical information handling system that uses physical principles and media to imitate the structure of human brain nerve cells and the way of information transmission [8]. The artificial neural network is shown in Figure 1.

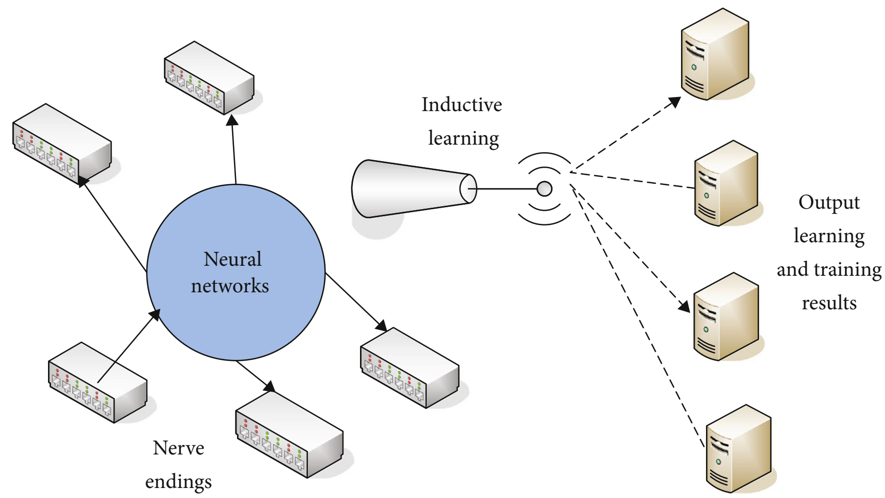


Figure 1: Artificial neural network.

3.2. BP Neural Network. The BP neural network is one of the many types of artificial neural networks, and it is the abbreviation of the feedforward neural network with reverse propagation of errors [9]. The BP neural network is currently the most mature and widely used neural network model. It is mainly used in the fields of function approximation, accurate pattern classification and recognition, and data compression. The full name of the BP neural network is backpropagation network. The reason why it has this name is that the adjustment rule of its network weights adopts the backpropagation learning algorithm, that is, the BP learning algorithm. The BP learning algorithm is a multilayer network that uses nonlinear differentiable functions for weight training. The BP neural network has simple structure, strong plasticity, clear mathematical meaning, and clear learning algorithm steps. It has been widely used in the fields of function approximation, accurate pattern recognition and classification, learning classification, and data compression [10]. According to statistics, 85%-90% of the neural network models use the BP neural network or its variations, and the BP network embodies the most critical part of the artificial neural network theory. Studies have shown that 3-layer BP neural networks can approximate functions with arbitrary precision. The learning process of the BP neural network consists of two parts: forward propagation and backpropagation of input data and information. In the forward propagation process, the input samples are processed from the input layer through the hidden layer and transmitted to the output layer, in which the neuron state of each layer only affects the neuron state of the next layer. As a typical feedforward network, the BP neural network arranges neurons in layers: the first layer is the input layer, the second layer is one or more hidden layers, and the last layer is the output layer. Each layer of neural units can only connect to and transmit information to the adjacent neural unit layers. During the construction of the system, two different learning signals are transmitted from the positive and negative directions, and the information contained in the input variable is transmitted in the forward direction, from the input layer to the hidden layer and then from the output layer. The adjustment of the information transmitted by the neurons in each layer depends only on the output of the neurons in the previous layer. If the expected value cannot be output at the output layer, it turns to backpropagation. At this time, the error signal propagates from the output layer to the input layer and adjusts the connection weights of each layer and the bias value of the neurons in each layer along the way, so that the error signal is continuously reduced. In the process of actually dealing with the problem, after repeated iterations, when the error reaches the expected value, the training process of the BP neural network is ended. In short, the BP neural network model transforms the problem that needs to be solved with input variables and output results into the problem of nonlinear functions to find the optimal solution. Such a model can be viewed as a mapping from input to output, which itself is highly nonlinear [11, 12]. The basic structure of the BP neural network is shown in Figure 2.

3.3. BP Learning Algorithm. The learning method of the BP neural network is supervised learning, and the training process needs to provide input vector a and expected output b. During the training process, the weights and biases of the network are adjusted according to the network error performance, and the desired function is finally achieved. The forward neural network still uses the mean square error as the default network performance function, and the process of network learning is the process of minimizing the mean square error [13].

There is an n-layer neural network, the input variables are input in a specific way P, and the sum of the input information of the m-th cell unit of the c-th layer of the neural network is U_m^c. And use V_m^c to represent the result of the m-th neural cell unit and use W_{mj} to represent the relationship weight between the m-th neural cell unit in this layer and the result of the j-th neural cell in the upper layer, and f represents the functional relationship between the input information and the output information. Then, the

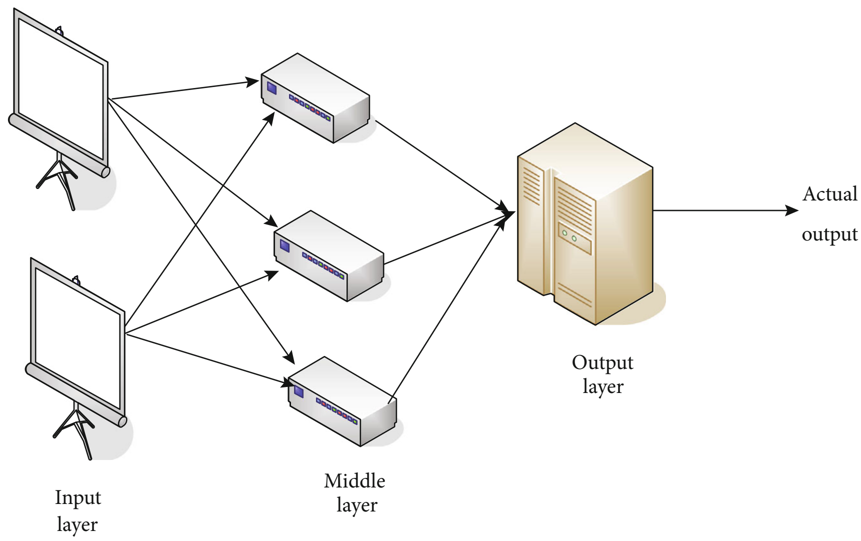


Figure 2: BP neural network structure.

relationship between the input and output variables is as follows [14]:

$$V_m^c = f\left(U_i^k\right), \tag{1}$$

$$U_m^c = \sum_j w_{mj} V_m^{c-1}. \tag{2}$$

First, use the function g to represent the error function, which means that the sum of the squares of the difference between the actual output result and the expected result is set as expected:

$$g = \frac{1}{2}\sum_j \left(V_j^n - y_j\right)^2. \tag{3}$$

y_j in the formula represents the expected output value of the entire neural network model and v_j^n represents the actual result of the system after information transmission, which is a function obtained according to the connection weight and input method. The main significance of this expression is to make the actual output result approach the expected output value by finding the minimum value of the error function. In order to achieve the solution purpose, a nonlinear programming method can be used to make the error function decrease rapidly along the gradient direction [15]. The update amount Δw_{mj} of its weight w_{mj} is as follows:

$$\Delta w_{mj} \infty - \varepsilon \frac{\alpha g}{\partial w_{mj}}. \tag{4}$$

Get $\alpha g/\partial w_{mj}$, because

$$\frac{\partial U}{\partial w_{mj}} = \frac{\partial}{\partial w_{mj}}\left(\sum_j w_{mj} V_m^{c-1}\right). \tag{5}$$

Then,

$$\frac{\partial g}{\partial w_{mj}} = \frac{\partial g}{\partial Um} V_m^{c-1}, \tag{6}$$

getting

$$\Delta w_{ij} = -\varepsilon d \frac{\partial g}{\partial U w_{nj}} v_m^{c-1}, \tag{7}$$

which is

$$d_j^m = \frac{\partial g}{\partial U_j^m}, \tag{8}$$

assuming

$$\Delta w_{mj} = -\varepsilon d V_{mj}^{c-1}. \tag{9}$$

In the formula, ε represents the parameter of the learning rate and takes a positive value. And Δw_{mj} represents the obtained parameter update value. Find the formula for d_j^m:

$$d_j^m = \frac{\partial g}{\partial U_j^m}, \tag{10}$$

which is

$$d_j^m = \frac{\partial g}{\partial V_{mj}^{c-1}} \bullet \frac{\partial V_j^m}{\partial U_j^m}. \tag{11}$$

And if $f(U_j^m)$ is taken as a nonlinear function, then

$$f\left(U_j^m\right) = \frac{1}{1 + \exp\left(-U_m^c\right)}, \tag{12}$$

$$f\left(U_j^m\right) = V_j^m\left(1 - V_m^c\right). \tag{13}$$

If m is not a neural cell unit of the output layer but is located in the hidden layer, the situation is as follows:

$$\frac{\partial g}{\partial V_j^m} = \sum_m \frac{\partial g}{\partial U_m^{c+1}} W_{mj}, \tag{14}$$

which is

$$\frac{\partial g}{\partial V_j^m} = \sum W_{mj} \cdot d_m^{c+1}. \tag{15}$$

The calculated final output value is then

$$d_m^c = V_j^m\left(1 - V_j^m\right) \cdot \sqrt{W_{mj}} d_m^{c+1}. \tag{16}$$

After calculation, it can be concluded that the error signal d_j^m of the c layer is proportional to the error signal of the $m-1$ layer, indicating that they are adjusted in the same direction. It can be concluded from the calculation process that the signal transmission principle of the BP neural network is to compare the actual output V_j^m obtained by the forward transmission of the independent variable with the expected output value to obtain the error function. And through a series of parameter adjustments, the connection weights are modified to reduce as much as possible the error between the actual result and the desired result [16]. The process of the entire BP learning algorithm can be shown in Figure 3.

4. Experiment of Accounting Information Disclosure and Financial Crisis Beforehand Warning Based on the Artificial Neural Network

4.1. Experimental Method. The experimental methods and main steps adopted in this experiment are as follows: First, the main method of the experiment is to establish an accounting information disclosure test and financial crisis beforehand warning model based on the artificial neural network BP learning algorithm, and use this model to conduct experiments and analysis of accounting information disclosure and financial crisis beforehand warning. Secondly, the experimental object selected in this experiment is company H, a listed company in Shenzhen, hereinafter referred to as company H. After determining the experimental objects, relevant indicators are selected and data processing is carried out in combination with the experimental requirements. Then the experiment is carried out on the model training and testing of accounting information disclosure test and financial crisis early warning model established by BP learning algorithm based on the artificial neural network. And through calculation, it is judged whether the disclosure of accounting information is more in line with the norms after the training and testing of the accounting information disclosure test and financial crisis early warning model established by the BP learning algorithm based on the artificial neural network, and the accuracy rate of financial early warning for listed companies. This leads to the experimental conclusion [17].

4.2. Experiment Index Selection and Data Handling

(1) Selection of experimental indicators

This experiment mainly selected the following four specific accounting and financial indicators of H company: profitability index, solvency index, operating ability index, and development ability index [18], as shown in Table 1.

The four indicators in Table 1 can comprehensively reflect the financial information of H company in four aspects, including profitability, solvency, operating ability, and development ability, which meet the needs of the experiment. Next, the relevant data in the selected indicators should be processed, and the processed data will be used as the input value for the accounting information disclosure test and financial crisis beforehand warning model of test and training constructed based on the BP algorithm [19].

(2) Data handling

The relevant data in the index selected in the experimental index selection step is used as the input value of the accounting information disclosure test and financial crisis early warning model training and testing established based on the BP learning algorithm. And the experiment will screen and classify the accounting information disclosure data and financial crisis warning data of H company from 2018 to 2021. The screening and classification of data mainly follow the principle of correlation between the data and the company's financial crisis information. The data with higher correlation with the company's financial crisis information has higher testing value for this experiment. Although the artificial neural network has strong information handling ability, if the input financial data is not enough, the accounting information disclosure test and financial crisis beforehand warning model constructed by the BP learning algorithm based on the artificial neural network cannot play its own advantages. Therefore, in order to avoid errors caused by insufficient financial indicator data, it is necessary to repeatedly screen and classify as much data as possible to reduce errors as much as possible [20].

4.3. Accounting Information Disclosure Test Based on the BP Learning Algorithm Test Model. First, the accounting information disclosure test and financial crisis beforehand warning model constructed based on the artificial neural network BP learning algorithm in this experiment are shown in Figure 4.

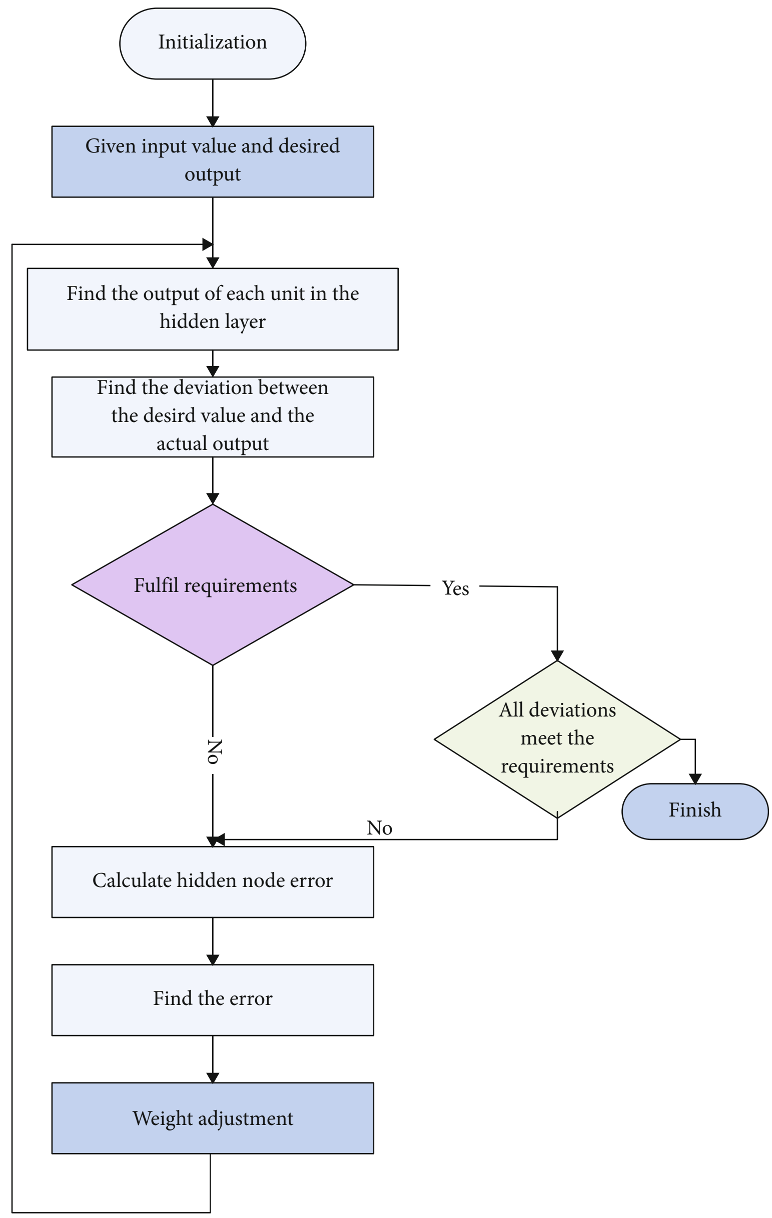


Figure 3: BP learning algorithm flow.

Table 1: Experimental indicators.

Index	Instruction
Profitability	Reflects the capital appreciation ability of an enterprise and is the core of all financial indicators of an enterprise
Solvency	Reflects the short-term and long-term solvency of an enterprise, including indicators such as current ratio and asset-liability ratio
Operating capacity	Be used to measure the management efficiency of corporate finance and the effectiveness of corporate asset utilization
Development ability	Reflects the financial growth ability of the enterprise and is obtained through the inspection of indicators such as the growth rate of total assets and the growth rate of operating income

The model in Figure 4 is relatively clear and shows the model testing and training process of the accounting information disclosure test and the financial crisis early warning experiment. Next, this paper will first conduct the accounting information disclosure test based on the BP learning algorithm accounting information disclosure test and

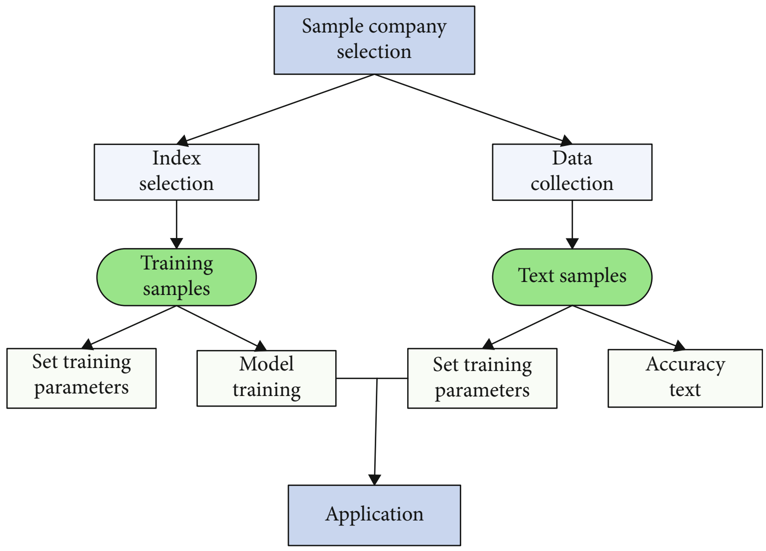
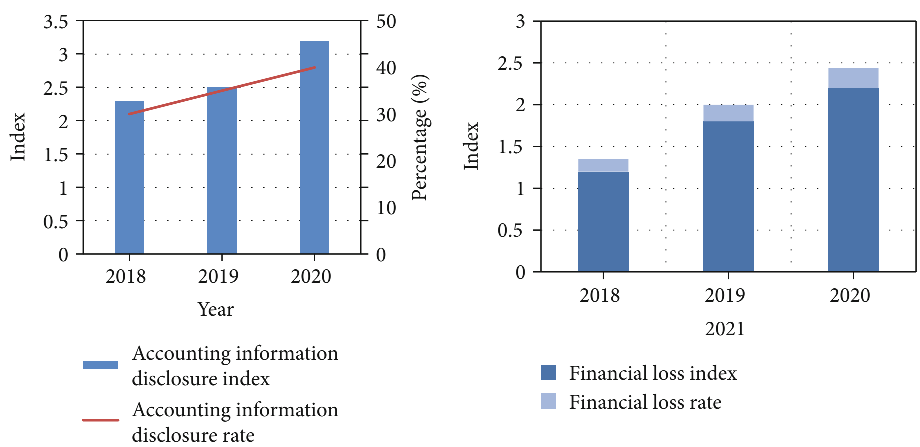


Figure 4: BP learning algorithm accounting information disclosure test and financial crisis beforehand warning model.



(a) Accounting information of company H in 2018-2020

(b) Noncompliant accounting information of company H in 2018-2020

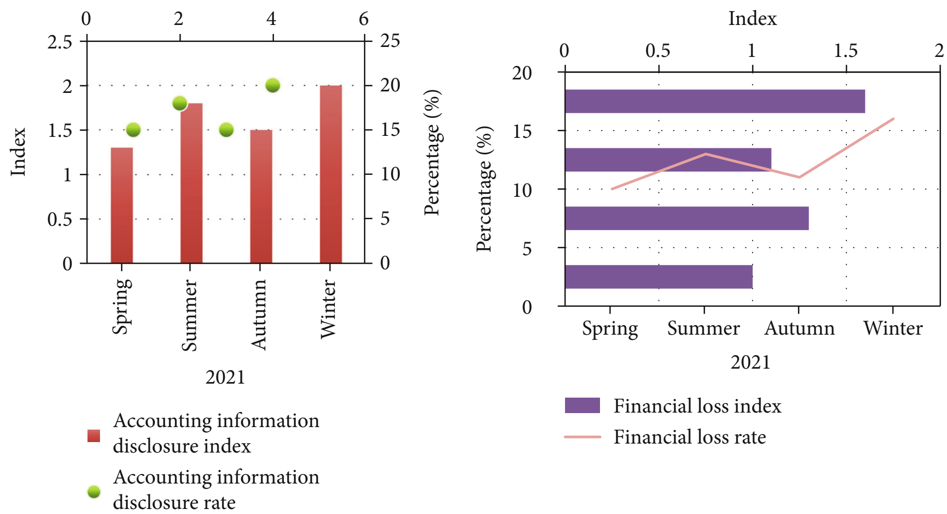
Figure 5: Accounting information disclosure data of H company from 2018 to 2020.

financial crisis beforehand warning model. The purpose of this accounting information disclosure test is to test whether the BP learning algorithm model based on the artificial neural network is effective in reducing the noncompliant accounting information disclosure rate. So the main steps of the test are as follows: first selecting the accounting information disclosure rate of H company from 2018 to 2020 and the company's financial loss data due to noncompliant accounting information disclosure and then comparing with the company' s accounting information disclosure rate based on the BP learning algorithm model in the four quarters of 2021 and the company' s financial loss data due to noncompliant accounting information disclosure during this period. Finally, through the comparison results, it is judged whether the accounting information disclosure test model based on BP learning algorithm is effective in reducing the noncompliant accounting information disclosure rate and thus reducing the financial loss caused to the company. First, the accounting information disclosure rate of H company from 2018 to 2020 and the financial loss data caused by noncompliant accounting information disclosure to the company are shown in Figure 5.

From Figure 5, it can be concluded that between 2018 and 2020, the maximum accounting information disclosure rate of company H was 40% of that in 2020. Among them, the largest financial loss rate caused by noncompliant accounting information disclosure to the company is 24%.

The accounting information disclosure rate of company H based on the BP learning algorithm model during the four quarters of 2021 and the company's financial loss data due to noncompliant accounting information disclosure during this period are shown in Figure 6.

As can be seen from Figure 6, after the testing and training of the accounting information disclosure test model



(a) Accounting information of company H between the four major quarters of 2021

(b) Noncompliant accounting information of company H between the four major quarters of 2021

Figure 6: Accounting information disclosure data of company H in the four quarters of 2021 based on the BP learning algorithm model.

based on the BP learning algorithm, the maximum accounting information disclosure rate of H company in 2021 will be 20% in autumn. The largest financial loss rate for the company due to noncompliant accounting information disclosure was 16% in winter. It is not difficult to compare these data with the relevant data of H company from 2018 to 2020. Compared with 2020, the maximum accounting information disclosure rate of H company in 2021 will drop by 20%. The maximum financial loss rate for companies due to noncompliant accounting disclosures was reduced by 8%. This also reflects that after the testing and training of the accounting information disclosure test model based on the BP learning algorithm, the noncompliant accounting information disclosure rate of H company in 2021 will be significantly lower than that in 2020. That is to say, the accounting information disclosure test model based on the artificial neural network BP learning algorithm has a good effect in reducing the noncompliant accounting information disclosure rate and thus reducing the financial loss caused to the company.

4.4. Financial Crisis Beforehand Warning Experiment Based on the BP Learning Algorithm Beforehand Warning Model. Next, this paper will carry out the beforehand warning experiment of H company's financial crisis based on the BP learning algorithm beforehand warning model. The basic steps taken in this financial crisis beforehand warning experiment are as follows: first, extracting the financial crisis data of H company from 2018 to 2020 and the corresponding financial crisis beforehand warning accuracy data. Then, the financial crisis beforehand warning model established based on the artificial neural network BP learning algorithm is for testing and training the relevant financial data and financial crisis beforehand warning data of H company in the first three quarters of 2021. Afterwards, the company's financial crisis warning for the fourth quarter was remade. After verification, the precision rate of financial crisis beforehand warning for the fourth quarter of 2021 was calculated and compared with the average financial crisis beforehand warning rate of company H from 2018 to 2020. Therefore, it is judged that the financial crisis beforehand warning model based on the artificial neural network BP learning algorithm is effective for the financial crisis beforehand warning of listed companies.

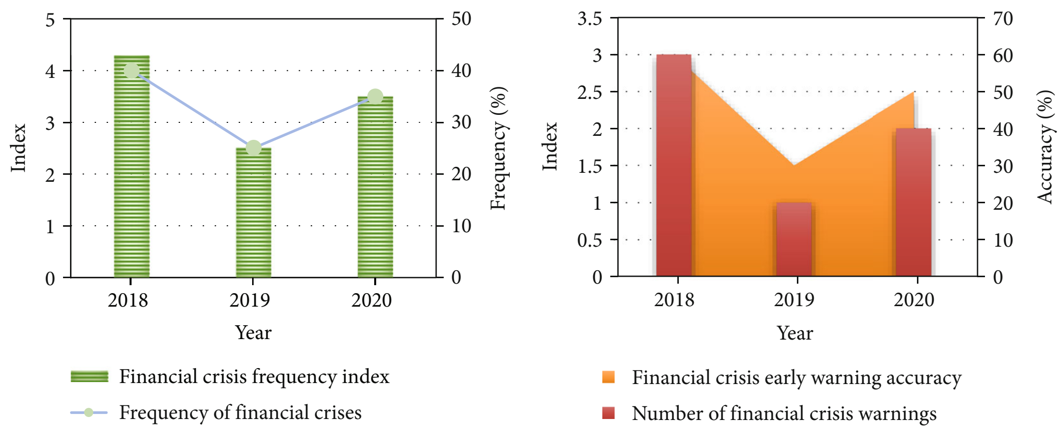
First, the 2018-2020 financial crisis data of company H and the corresponding financial crisis beforehand warning accuracy data are exhibited in Figure 7.

It can be seen from Figure 7 that between 2018 and 2020, company H experienced the most financial crisis in 2018. At that time, the frequency index of financial crisis was 4.3, and from 2018 to 2020, the highest precision rate of financial crisis beforehand warning of H company was also in 2018, and the beforehand warning accuracy rate was 60%. The average financial crisis beforehand warning accuracy rate of H company from 2018 to 2020 was 55%.

After using the financial crisis beforehand warning model in view of the artificial neural network BP learning algorithm to conduct certain tests and training on the relevant financial data and financial crisis beforehand warning data of H company in the first three quarters of 2021, the results are shown in Table 2.

The data in Table 2 shows that among the four major quarters of 2021, the number of financial crises in the spring is the highest, and the accuracy of financial crisis warnings in the winter is the highest. Combined with the results of Table 2, after the company's financial crisis warning for the fourth quarter is remade, the financial crisis and financial crisis warning accuracy data of company H in the four quarters of 2021 are shown in Figure 8.

It can be concluded from Figure 8 that among the financial crisis and beforehand warning data of company H in the four quarters of 2021 based on the artificial neural network BP



(a) Financial crisis data of H company in 2018-2020

(b) Financial crisis beforehand warning data of H company in 2018-2020

Figure 7: 2018-2020 H company financial crisis and crisis warning data.

Table 2: Test and training results of the financial crisis beforehand warning model.

Season	Number of crises that occurred	Crisis warning accuracy
Spring	30	60%
Summer	20	50%
Autumn	23	80%
Winter	15	90%

learning algorithm beforehand warning model, the financial crisis occurred most frequently in spring, with a frequency of 30%. The highest accuracy rate of beforehand warning of financial crisis was 90% in winter. From this, it can be concluded that the accuracy of the financial crisis beforehand warning rate of company H in 2021 is 35% higher than that of the average financial crisis beforehand warning rate of company H in the three-year period from 2018 to 2020. This shows that the financial crisis beforehand warning model based on the artificial neural network BP learning algorithm has a good effect on the company' s financial beforehand warning, and the beforehand warning accuracy has been improved.

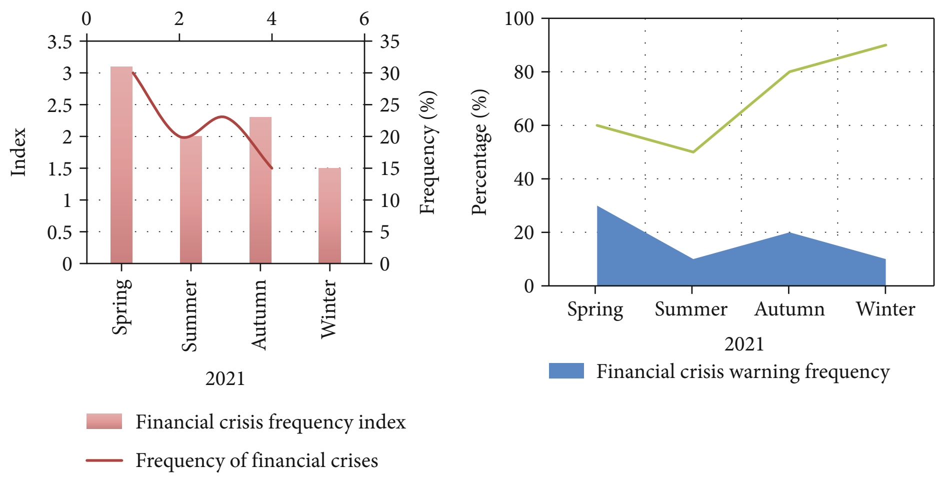
This is the end of the whole experiment. Combining the experiments, the following conclusions can be drawn: the accounting information disclosure test and the financial crisis beforehand warning model in view of the artificial neural network BP learning algorithm are more effective in reducing the company' s noncompliant accounting information disclosure, reducing the financial loss caused to the company and improving the accuracy of the company's financial crisis beforehand warning. By reducing the disclosure rate of noncompliant accounting information, the company's financial loss has been reduced by 8%, and the accuracy of the company's financial crisis warning has also increased by 35%. This has certain reference significance for the application value of accounting information disclosure test and financial crisis early warning model based on the artificial neural network BP learning algorithm.

5. Discussion

With the continuous development of the social economy and the continuous changes of the global economic situation, the financial crisis has become a problem that enterprises have to face and can most threaten the survival and development of enterprises. If the financial crisis that will appear in the enterprise cannot be more accurately warned and timely measures are not taken to avoid the crisis, the enterprise is likely to face huge financial losses, which will directly affect the survival and development of the enterprise [21]. However, in order to improve the accuracy of early warning of corporate financial crisis and take timely measures to avoid the crisis, advanced methods and technical support are inseparable.

The artificial neural network is a mathematical model that imitates a biological neural network for information handling. It has powerful information and data handling capabilities. The BP neural network is one of the many artificial neural networks. It is a feedforward neural network with reverse propagation of errors and is widely used. The BP learning algorithm based on the BP neural network is a supervised learning and training algorithm, which outputs the expected value by continuously adjusting the weight of the input value and reducing the error [22].

This paper establishes an accounting information disclosure test and financial crisis early warning model based on the artificial neural network BP learning algorithm. And based on this model, the accounting information disclosure test and financial crisis early warning experiment are carried out, taking the accounting information disclosure and financial crisis early warning situation of H company from 2018 to 2021 as an example. The experimental conclusion is shown as follows: the accounting information disclosure test and the financial crisis beforehand warning model in view of the artificial neural network BP learning algorithm are relatively effective in reducing the company's noncompliant accounting information disclosure, thereby reducing the financial loss caused to the company and improving the accuracy of the company's financial crisis beforehand warning.



(a) Financial crisis data of company H in the four quarters of 2021

(b) Financial crisis warning data of company H in the four quarters of 2021

Figure 8: Financial crisis and beforehand warning data of H company in the four quarters of 2021 based on the BP learning algorithm beforehand warning model.

6. Conclusion

Based on the research subject of accounting information disclosure and financial crisis beforehand warning based on the artificial neural network, this paper establishes an accounting information disclosure test and financial crisis beforehand warning model in view of the artificial neural network BP learning algorithm. And this paper carried out the relevant accounting information disclosure test and financial crisis beforehand warning experiment. Finally, it is found that the accounting information disclosure test and financial crisis beforehand warning model based on the artificial neural network BP learning algorithm are both effective in reducing the company's noncompliant accounting information disclosure, thereby reducing the financial loss caused to the company and improving the accuracy of the company' s financial crisis beforehand warning. The research in this paper provides a certain degree of reference for the application of artificial neural network technology in accounting information disclosure and financial crisis early warning. It is hoped that this paper can play a certain role in promoting the research on accounting information disclosure and financial crisis early warning based on the artificial neural network.

However, due to the limited research conditions and level of this paper, there are still some deficiencies in the research of this paper; for example, the innovation of research methods needs to be improved. It is believed that there will be more excellent researches on the application of the artificial neural network in accounting information disclosure and financial crisis warning in the future.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

References

[1] A. Y. Alanis, "Electricity prices forecasting using artificial neural networks," *IEEE Latin America Transactions*, vol. 16, no. 1, pp. 105–111, 2018.

[2] E. Isik and M. Inalli, "Artificial neural networks and adaptive neuro-fuzzy inference systems approaches to forecast the meteorological data for HVAC: the case of cities for Turkey," *Energy*, vol. 154, no. 7, pp. 7–16, 2018.

[3] A. Khorasani and M. Yazdi, "Development of a dynamic surface roughness monitoring system based on artificial neural networks (ANN) in milling operation," *The International Journal of Advanced Manufacturing Technology*, vol. 93, no. 1-4, pp. 141–151, 2017.

[4] M. Safa, S. Samarasinghe, and M. Nejat, "Prediction of wheat production using artificial neural networks and investigating indirect factors affecting it: case study in Canterbury Province, New Zealand," *Journal of Agricultural Science and Technology*, vol. 17, no. 4, pp. 791–803, 2018.

[5] B. Tarawneh, "Predicting standard penetration test *N*-value from cone penetration test data using artificial neural networks," *Geoscience Frontiers*, vol. 8, no. 1, pp. 199–204, 2017.

[6] S. Li, M. Fairbank, C. Johnson, D. C. Wunsch, E. Alonso, and J. L. Proao, "Artificial neural networks for control of a grid-connected rectifier/inverter under disturbance, dynamic and power converter switching conditions," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 4, pp. 738–750, 2014.

[7] F. Ascione, N. Bianco, C. De Stasio, G. M. Mauro, and G. P. Vanoli, "CASA, cost-optimal analysis by multi-objective optimisation and artificial neural networks: a new framework for the robust assessment of cost-optimal energy retrofit, feasible

for any building," *Energy and Buildings*, vol. 146, no. 7, pp. 200–219, 2017.

[8] S. H. Alemohammad, B. Fang, A. G. Konings et al., "Water, energy, and carbon with artificial neural networks (WECANN): a statistically based estimate of global surface turbulent fluxes and gross primary productivity using solar-induced fluorescence," *Biogeosciences*, vol. 14, no. 18, pp. 4101–4124, 2017.

[9] S. Hiroki, "Method to solve quantum few-body problems with artificial neural networks," *Journal of the Physical Society of Japan*, vol. 87, no. 7, pp. 074002–074100, 2018.

[10] M. D. Damavandi, H. Safikhani, and M. Yahyaabadi, "Multi-objective optimization of asymmetric v-shaped ribs in a cooling channel using CFD, artificial neural networks and genetic algorithms," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 39, no. 6, pp. 319–329, 2017.

[11] A. Lino, Á. Rocha, and A. Sizo, "Virtual teaching and learning environments: automatic evaluation with artificial neural networks," *Cluster Computing*, vol. 22, no. 4, pp. 1–11, 2017.

[12] G. Canziani, R. Ferrati, C. Marinelli, and F. Dukatz, "Artificial neural networks and remote sensing in the analysis of the highly variable Pampean shallow lakes," *Mathematical Biosciences & Engineering Mbe*, vol. 5, no. 4, pp. 691–711, 2017.

[13] G. H. Bazan, P. R. Scalassara, W. Endo, A. Goedtel, W. F. Godoy, and R. H. C. Palácios, "Stator fault analysis of three-phase induction motors using information measures and artificial neural networks," *Electric Power Systems Research*, vol. 143, no. 2, pp. 347–356, 2017.

[14] D. G. Giovanis, I. Papaioannou, D. Straub, and V. Papadopoulos, "Bayesian updating with subset simulation using artificial neural networks," *Computer Methods in Applied Mechanics and Engineering*, vol. 319, no. 6, pp. 124–145, 2017.

[15] Z. Aram, S. Jafari, J. Ma, J. C. Sprott, S. Zendehrouh, and V. T. Pham, "Using chaotic artificial neural networks to model memory in the brain," *Communications in Nonlinear Science and Numerical Simulation*, vol. 44, no. 4, pp. 449–459, 2017.

[16] B. Khoshnevisan, S. Rafiee, J. Iqbal et al., "A comparative study between artificial neural networks and adaptive neuro-fuzzy inference systems for modeling energy consumption in greenhouse tomato production-a case study in Isfahan Province," *Journal of Agricultural Science and Technology*, vol. 17, no. 1, pp. 49–62, 2018.

[17] M. Dimitrijević, M. Andrejević-Stošović, J. Milojković, and V. Litovski, "Implementation of artificial neural networks based AI concepts to the smart grid," *Facta universitatis - series: Electronics and Energetics*, vol. 27, no. 27, pp. 411–424, 2017.

[18] A. A. Mas'ud, J. A. Ardila-Rey, R. Albarracín, F. Muhammad-Sukki, and N. A. Bani, "Comparison of the performance of artificial neural networks and fuzzy logic for recognizing different partial discharge sources," *Energies*, vol. 10, no. 7, pp. 10–60, 2017.

[19] Y. Fei, J. Hu, W. Q. Li, W. Wang, and G. Q. Zong, "Artificial neural networks predict the incidence of portosplenomesenteric venous thrombosis in patients with acute pancreatitis," *Journal of Thrombosis and Haemostasis*, vol. 15, no. 3, pp. 439–445, 2017.

[20] A. I. Ivanov, P. S. Lozhnikov, and A. E. Sulavko, "Evaluation of signature verification reliability based on artificial neural networks, Bayesian multivariate functional and quadratic forms," *Computer Optics*, vol. 41, no. 5, pp. 765–774, 2017.

[21] G. Perchiazzi, C. Rylander, M. Pellegrini, A. Larsson, and G. Hedenstierna, "Monitoring of total positive end-expiratory pressure during mechanical ventilation by artificial neural networks," *Journal of Clinical Monitoring and Computing*, vol. 31, no. 3, pp. 551–559, 2017.

[22] A. H. Sebayang, H. H. Masjuki, H. C. Ong et al., "Optimization of bioethanol production from sorghum grains using artificial neural networks integrated with ant colony," *Industrial Crops and Products*, vol. 97, no. 7, pp. 146–155, 2017.